PREDICTION OF DIABETIC RETINAL DISEASE AND GLAUCOMA AMONG DIABETIC COMMUNITY USING SOFT COMPTING TECHNIQUES

A SYNOPSIS

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1. INTRODUCTION

In recent decades, there has been a significant rise in morbidity related to diabetes. The retina detects light to generate electrical impulses that the brain uses to analyze and interpret visual information. Diabetic retinal disease and glaucoma are common eye diseases associated with diabetes, leading to varying degrees of vision loss. According to World Health Organization [1], 43 million individuals have medium to severe visual impairments due to diabetic retinal disease, glaucoma, and central glaucoma [2],[3]. To prevent the consequences of chronic diseases like diabetes, early diagnosis is crucial.

Computer-Aided Diagnostic (CAD) systems typically employ retinal images to support Ophthalmologists in making assessments through Machine Learning (ML) Models[4]. The scientific community has published several Artificial Intelligence (AI) based techniques for identifying diabetic retinal disease and glaucoma using retinal fundus images[5]. Fundus image is a popular, fast, noninvasive, and well-tolerated imaging method. It is among the most widely used techniques to assess the degree of diabetic retinal disease and glaucoma.

Early treatment to conditions like glaucoma and diabetic retinopathy can effectively reduce the evolution of the disease and stop irreversible visual loss [6]. As a result, prevention of vision issues such as diabetic retinopathy, glaucoma, and Age-Related Macular Degeneration (AMD) depends on efficient screening and early detection. Additionally, the degree of treatment recommended is determined by the severity of diabetic retinal disease and glaucoma. Early and efficient diabetes control can prevent vision loss instead of requiring patients to have costly laser surgery [7]. More accurate systems could detect diabetic retinal disease and glaucoma earlier, allowing patients to receive treatment and avoid blindness. In developing regions, manual diagnosis often fails to reach the recommended 80% sensitivity, while patient-to-expert ratios are reported to be balanced.

Diabetic retinal disease and glaucoma can be detected at different stages using timely detection services for retinal abnormalities and diseases. However, traditional manual disease analysis techniques are time-consuming, labor-intensive, and error-prone. Furthermore, they frequently call for complex task teams, which might only be possible with the current situation. However, manual detection is not feasible for the

early identification of diabetic retinal disease and glaucoma [8],[9]. Tests for retinal disorders require specialized attention and expertise. Large populations lack qualified Ophthalmologists to perform these demanding tasks. However, the rapid development of digital applications and data-driven techniques has increased the popularity of AI-based clinical screening systems. These systems offer a practical and cost-effective approach to automatically analyzing retinal diseases.

The initial approach, the Random Search Optimization Adaboost Ensemble (RSOAE) algorithm and Bayesian Optimization Support Vector Machine (BOSVM), are supervised learning and active learning workflow enable the identification of latent structures within the patient's data. This is quite important, especially when analysing data from diabetics, since complications resulting from diabetes and those of glaucoma have many similarities. The incrementally adaptive character updates the model in real-time depending on the shifts in the data distribution robustness. Further, it uses ensemble techniques to provide multiple prediction models to increase precision and thorough variance reduction to provide generalization with new data.

Deep Neural Network (DNN) model is used to classify retinal disease from the risk factors dataset. A DNN is a class of ANN where the layers between input and output layers are hidden, and it has gained tremendous success in recent classifications. A DNN is fully connected layer which make connections of each layer will be linked to all the units in the previous layer.

The proposed method of Faster Region-based Convolutional Neural Network-Artificial Algae Algorithm with Support Vector Machine (FRCNN-AAASVM) for screening glaucoma could enhance glaucoma detection in the early stages. Employing fundus images may provide healthcare providers with an early interventional avenue to prevent vision loss due to glaucoma and be a less costly and efficient detection method.

The more refined method is the Explainable Artificial Intelligence Hybrid Stacking Ensemble Classification (EAIHSEC) model, which integrates data-driven and image-driven insights to refine the prediction procedure. This combined approach begins by passing over the retinal images through a deep learning (DL) model to obtain features linked with glaucoma. Thus, combining the EAIHSEC method with the glaucoma prediction methods allows for overcoming this weakness by improving

the interpretability of the feature learning and significantly impacting the early diagnosis of glaucoma and subsequent application of the individual approach to the diabetic patients.

2. LITERATURE SURVEY

Ikram et al. [10] reviewed ML assessment method to categorize and detect diabetic retinal disease. The present study uses fundus images from publicly available diabetic retinal datasets. However, manually identifying diabetic retinal disease and glaucoma from fundus images is difficult and prone to errors. The tested dataset is trained and validated based on a DL model to evaluate the test image's quality Bajwa et al. [11] designed intelligent system. It protects the patient's vision and offers an easy and effective approach to the early detection of exudates in diabetic retinal disease and glaucoma. Malhi et al. [12] found high blood sugar can cause blindness because it damages the blood vessels in the eyes.

To forecast the severity of diabetic retinal disease and glaucoma, Oulhadj et al. [13] presented a DL technique based on appropriate visual modifiers and a modified capsule network. Additionally, pre-processing images using the Contrast-Limited Adaptive Histogram Equalization (CNN) technique improves the model for computer vision performance. Butt et al. [14] made an hybrid method for classifying fundus pictures for glaucoma and diabetic retinal disease is suggested. This method extracts ensemble features using a pre-trained Convolutional Neural Network (CNN) technique. However, elevated blood sugar levels in people with diabetes may impact the blood vessels in the retina. Dai et al. [15] are created to grade 466,247 fundus photos from diabetic patients, detect lesions, and evaluate image quality in real time. Furthermore, they analyzed 209,322 images are compared to provide three diabetic retinal disease and glaucoma datasets and a local collection of 200,136 fundus images

Meruva et al. [16] analyzed the collected information to evaluate the processing results for 5,500 fundus images obtained from the diabetic retinopathy and glaucoma dataset. Diabetes predicted and classified from retinal images based on a proposed Mahmoud et al. [17] proposed Deep Neural Network (DNN), which preprocesses, normalizes the retinal dataset to predict diabetes. Ujwala et al. [18] explained how angiography is most essential pre-operative procedures for early detection of retinal disorders. Hacisoftaoglu et al. [19] assessed the impact of using

funds images from several datasets using a ResNet50 technique based on transfer learning. It also predicts the accuracy of diabetes diagnosis using fundus images from the dataset.

Table 1 Literature survey on prediction of diabetic retinal disease and glaucoma using retinal fundus images

Author, Year	Method	Dataset	Performance Evaluation	Limitation	Accuracy
Asia et al. [20]. 2021	ResNet-50, VggNet-16	Xiangya No.2 Hospital Ophthal mology (XHO)	ROC, Positive Predictive Value (PPV)	Predicting diabetic retinal disease and glaucoma via manual detection is difficult and time-consuming due to its complexity .	91.4 %
Nazir et al. [21], 2020	DenseNet-100	Indian diabetic retinal disease and glaucoma Image Dataset (IDRiD)	Mean Average Precision (MAP)	Predicting effective screening-based treatments is a costly task	90.22%

Jabber et al. [22], 2024	VGG Net	MESSIDOR	Precision	Number of undetected cases	91.2%
Bilal et al. [23], 2024	Improved Support Vector Machine-Radial Basis Function (ISVM-RBF)	IDRiD	Specificity	Severe outcomes of diabetic retinal disease and glaucoma illnesses	92.1%
Sunkari et al. [24], 2024	Mobile Net-V2	APTOS	Sensitivity	Retinal image classificati-on is difficult even for skilled clinicians	92.51%
Beghriche et al. [25], 2023	DenseNet121Mobile NetV2	APTOS 2019	Accuracy	expensive	91.7%

Table 1 presents an analysis of various methods for identifying diabetic retinal disease and glaucoma using retinal fundus images from the dataset, including significant details on dataset size, performance evaluation, limitations, and accuracy.

Diabetes prediction is stable and reliable because the diabetes datasets have few outliers and limited labelling data. Annamalai and Nedunchelian [26] proposed new method Optimal Weighted Based Deep Artificial Neural Network (OWDANN)

technique resolved the issue by additional training time and provided low detection accuracy. Many could avert preventable blindness if these anomalies were identified and treated early to stop future development. A Deep Convolutional Neural Networks (DCNN) approach used to achieve the goal. The suggested method is laborious, time-consuming, and not repeatable described by Muchuchuti and Viriri [27]. Diagnosing diabetes early is crucial and could save many lives It may become overly intricate and detailed, identifying noise in the data rather than underlying trends. Manually screening for diabetic retinal disease and glaucoma is a highly time-consuming and arduous process that primarily relies on qualified ophthalmologists. Bilal et al. [28] designed an automatic detection technique based on U-Net was used to fix the problem done. In classification problems with unbalanced datasets, it may be biased in favour of the prevailing class.

Most exiting results show that when the CNN-Long Short-Term Memory (CNN-LSTM) technique is applied as a network ensemble, the proposed model performs better than some current classification models by Khanna et al. [29]. Nazih et al. [30] proposed Vision Transformers (ViTs) model based on fundus images and achieved 82.5% accuracy.

3. OBJECTIVES

The core intention of this research is to develop the prediction model for diabetic retinal disease and glaucoma by enhancing accuracy, efficiency, and reducing error rate using machine learning, deep learning and interpretable explainable artificial intelligence. The following are the specific objectives:

- **Objective 1**: To develop a learning model for the prediction of diabetic retinal and glaucoma in diabetic populations, leveraging a comprehensive set of strong and potential risk factors.
- **Objective 2**: To design an optimized deep learning framework for predicting glaucoma through 2D fundus image to increase prediction accuracy.
- **Objective 3**: To develop a model that visualizes model reasoning, enabling Clinicians to understand the underlying logic behind the predictions.

4. RESEARCH PROBLEMS

- Diabetic retinal images are contains more dimensions because contrasting entities are not illuminated without the proper preprocessing and filter methods.
- The scaling features need to be more direct and could be more independent in reducing the boundary margin variations, which cause improper segmentation.
- Prevailing methods do not concentrate feature extraction to reduce the dimensionality of the image scaling, so the dimension reduces the identification accuracy.
- Improving accuracy requires for prediction model
- Developing explainable artificial intelligence model for quick decision making process for clinicians.
- Longitudinal studies and dynamic prediction giving less importance to track progression over time can provide valuable insights into disease dynamics and enable more accurate prediction future outcomes.

5. PROPOSED METHODOLOGY

In this section, we evaluated the effectiveness of the EAIHSE approach in predicting glaucoma and diabetic retinal disease using a different dataset. Additionally, 10-fold cross-validation with decision trees as the learner type and the random search AdaBoost optimizer without functions at a specified time was used to achieve the optimal solution. By analyzing the diabetic patient's dataset, retinal fundus images through RSOAE, BOSVM, DNN, FRCNN-AAASVM algorithms to early prediction of glaucoma and diabetic retinal disease. Lastly, based on all model comparison, EAIHSEC model is having superior efficacy in predicting glaucoma and diabetic retinopathy as diabetic retinal disease.

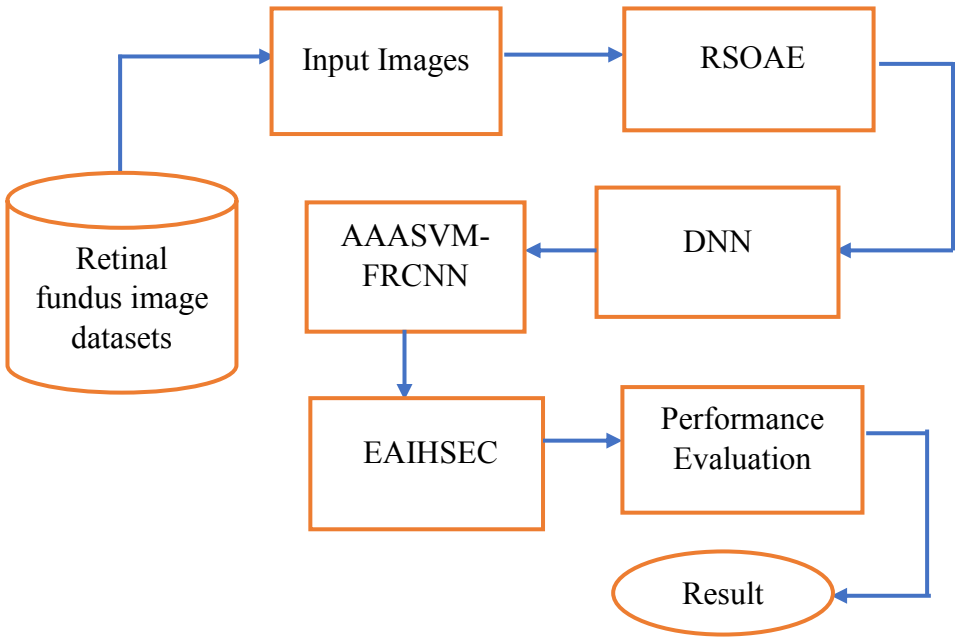

Figure 1. Overall architecture diagram

As shown in Figure 1, the effectiveness of the EAIHSEC model in forecasting diabetic retinopathy and glaucoma was evaluated critically using a real-time dataset. The presented model combines many predictive techniques to detect these common eye conditions and improve interpretation accuracy. These findings provide valuable insights into the efficacy of AI applications in medicine.

5.1 Dataset depiction

This section compiles medical records of diabetic patients to create a dataset of 2,450 records. Using these images as input, we design a system that can be clinically interpreted. We fitted the provided ensemble model using publicly accessible retinal fundus imaging datasets. The fundus images of diabetic retinal patients at risk for glaucoma are collected by an intelligence-based interpretive system, which uses an hybrid ensemble model to assess the reliability of the images. Using suggested segmentation and feature extraction techniques, visualize glaucoma and health images from datasets.

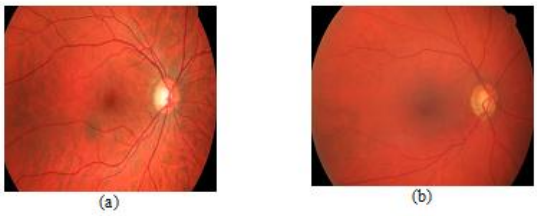

Figure 2. Retinal database images

Figure 2 shows fundus images of a standard and glaucomatous retina. The training image dataset comprises 196 fundus images from the public retina collection.

5.2 RSOAE, deep neural network intelligent support system for glaucoma among diabetic mellitus community

5.2.1 Preprocessing

The retinal dataset collected from the kaggle repository is cleaned and evaluated for data preprocessing. In addition, missing values are removed from the data by creating datasets for different levels. Furthermore, the analysis of high blood pressure and blood glucose levels, replaced by Cup-to-Disk Ratio (CDR) values, is performed. The values stored in this dataset are calculated and determined from the averages of the fundus images. Therefore, random forest methods are used in 29 cases to select features in the dataset.

5.2.2 RSOAE machine algorithm

To generate potential outputs on a given dataset, the RSOAE method evaluates the data through ensemble operations such as packing, soft boost, logging boost, RUSboost, and Adaboost. Moreover, the random search Adaboost optimizer yields the optimal solution in 10-fold cross-validation. Using hyperparameter tweaking, the learner type and collection function based on the decision tree algorithm can produce results within a specific time.

5.3 Diabetic retinal disease prediction based on DNN

The primary goal of the research was to compare numerous retinal fundus images with optical coherence tomography images to detect intraocular glaucoma in as many eyes as possible at a reasonable cost. Furthermore, digital image processing tools can combine fundus and optical coherence tomography images to evaluate retinal characteristics.

5.3.1 Image analysis for retinal fundus characteristics

Evaluating the retinal fundus image determined various features and geometric and temporal characteristics. Furthermore, multiple parameters, such as optic cup, optic disc, neuro retinal rim, and vessel size, such as CDR, ISNT, and rim-to-disc ratios, established the essential predictors of glaucoma in fundus images. In addition, retinal fundus images were segmented using two main techniques: Neural Image Optimization (NIO) and Otsu thresholding, which can classify images obtained from a uniform dataset.

5.3.2 Region-of-Interest

This section used retinal fundus images to extract Regions of Interest (ROI) with the most precise glaucoma-related properties. These regions of interest include structures such as the optic cup, intervertebral disc, optic nerve head, and blood vessels to predict retinal glaucoma. After that, the retinal fundus images were classified using OTSU thresholding and NIO-based clustering. Consequently, temporal and geometric features were extracted from the dataset for each classification. Retinal images can be categorized by DNCN logic using information derived from two segmentation stages. Additionally, the classification performance of the identified images was assessed using the information gathered from the dataset. Furthermore, the proprioceptive areas of the optic disc and macular layer are the focus of retinal fundus imaging. The region with the highest center of gravity is where the disc is visible in the middle of the retinal fundus image.

5.3.3 Segmentation

The three categories of segmentation and clustering Red, Green, and Blue (RGB) are used to identify the elements of an image that require processing. The crimson stream represents the disc area because of the disc's vivid color and apparent lack of blood vessels. Light cups can also be collected using a green stream. When the input data matrix is divided into clusters, the attributes of objects that belong to the same cluster are similar. Similarly, the assumption determines whether items belong to clusters with distinct characteristics. The provided matrix may be divided into clusters using a straightforward NIO clustering technique, which can then be applied to transfer learning.

5.3.4 Classification

A greyscale image can be converted to a binary image using Otsu Median Filtering. By presenting the image as two sets of pixels, this method distinguishes between the foreground and background pixels using a dichotomous waveform. Otsu thresholding requires determining the segmentation threshold and calculating the standard deviation of the source image. In a graphical representation, vertical lines show pixel intensity, and horizontal lines show color changes. Examine each image's distribution to determine the threshold that divides the disc from the optical cup. The standard deviation represents the departure from the mean, indicated by the graph's center point. The standard deviation can be added to the mean value to find the concentration.

5.4 Hybrid convolutional neural network optimization with an artificial algae algorithm for glaucoma screening using fundus image

The following procedures were followed to use the suggested framework in this real-world experimental study: 1) multilevel preprocessing; 2) segmentation, boundary detection, and localization using ternausnet OD 3) feature extraction with an FRCNN 4) classification with an FRCNN and adaptive gradient algorithm optimizer FRCNN (AFRCNN) 5) substitution of SVM for the softmax layer and AAA as an optimized parameter; 6) evaluation and optimization of the model with Friedman statistical analysis 7) utilizing various fundus datasets to test the optimizer Artificial Algae Algorithm with Support Vector Machine (AAASVM) in FRCNN-based glaucoma screening.

5.4.1 Multi-Level Preprocessing

Multi-level preprocessing significantly advances traditional preprocessing techniques by processing the input image according to metrics, including color constancy, input image enhancement, holomorphic filtration, and background component removal. When processing the retinal input image, these metrics produce an improved image for subsequent processing.

5.4.2 Faster region based convolutional neural network based feature extraction

Several feature extractions for image-based retrieval were discussed, which aided in creating novel feature extractions based on an FRCNN. This stage involves

feeding the ternausnet picture output to the FRCNN to extract texture, color, and shape features. In the FRCNN, an RPN is used instead of a selective search. ConvNet receives input photos and returns the value of the item, the feature map, and anchor boxes of various sizes. Each proposal is trimmed to the length of the bounding box by the ROI, a pooling layer that receives the previous proposals. Following this procedure, the softmax layer receives the last output. The RPN produces a sliding window on the extracted characteristics. This suggested approach facilitates the gradients of the feature vectors in the proper directions for quicker grouping, using stochastic gradient descent momentum as the solver.

5.4.3 Glaucoma screening using a modified RCNN and tuned AFRCNN

To forecast normal and abnormal retinal pictures and glaucoma, extracted feature maps are put into the FRCNN's classification layer. The recently implemented fully connected softmax and classification layers are used for proper categorization. The box regression layer provides the input image's boxes, which connects them using average pooling. An adaptive gradient technique is employed to improve classification accuracy and manually eliminate learning rate adjustments. Stochastic gradients, which adjust frequently occurring features over sporadic ones in previous observations, are connected to this optimization.

5.4.4 Support Vector Machine (SVM)

To improve anchor box performance, the softmax classifier in the RPN was swapped out for the SVM in this suggested study. SVM method can find optimal solutions worldwide, even with a few training instances. A multi-dimensional space is used to construct a suitable segregated hyperplane. This classifier's Radial Basis Function (RBF) kernel distinguishes between the foreground and background region boxes.

5.4.5 Artificial Algae Algorithm (AAA)

The creation of this method was motivated by the actions of microalgae. The amount of light algae absorbs to gather a nutrient determines their development. This algorithm generates artificial algal cells that mimic the life activity of natural algae. A collection of algae cells that make up the entire population form colonies. A series of algal cells that can be thought of as solution dimensions make up each algal group.

The cluster of algae travels in the direction of an area that is rich in nutrients. The algae colony migrates, adapts, and evolves to enhance its location. Placing the colony in the ideal spot yields the optimum response.

5.5 Diabetic retinal glaucoma based on data and image driven sustainable two stage interpretable hybrid stacking explainable ensembles

5.5.1 Preprocessing and segmentation

Preprocessing is the initial stage in enhancing image quality for segmentation, object detection, and classification. This preprocessing method highlights specific aspects of the image and eliminates unwanted ones, providing helpful elements that aid prediction. For preprocessing, the colour fundus images were transformed to greyscale after the original input image was normalized to the interval [0, 1]. The retinal contrast are calculated after the noise eliminated by a gaussian filter.

5.5.2 Statistical texture feature extraction through GLCM and GLRLM

An essential component of medical picture analysis is the extraction of texture features. This procedure follows image segmentation. Histogram equalization, the local binary method, greyscale, log, and autocorrelation techniques are various methods used to extract features. The suggested approach uses a co-occurrence matrix to extract the characteristics from the processed images. A Gray Level Co-Occurrence Matrix (GLCM) and a Gray Level Run-Length Matrix (GLRLM) extract the pixel value profiles of first. second, and higher order features from this image.

5.5.3 Glaucoma detection factors based on entropy and kurtosis statistical features

Typically, Rim-To-Disc Ratio (RDR) is utilized as a criterion for diabetic retinopathy and glaucoma. The segmented fundus images are used to calculate these features. Kurtosis and statistical entropy rely on the original FR image's grey value. The amount deducted from the optic disc and cup is the entropy of the limbal area. In this case, the entropy is recovered when the initial values from the green channel are restored.

5.5.4 Ensemble learning classifier

Eighteen features have been selected for further glaucoma categorization after feature extraction. Training and test sets are currently separated from the available data. A training set of class labels represents a target instance with numerous features (attributes). The model in the suggested approach is label-aware. As a result, supervised ML algorithm classifiers are being used to predict glaucoma. An ensemble learning classifier uses this method to enhance classification performance. Several strategies are combined into a single classification model using ensemble methods.

5.5.5 Hybrid stacking ensemble classifiers (HSEC)

This method illustrates the classification model that utilizes a collection of diverse weak ensemble learners. The model is created with 10-fold cross-validation and hyperparameter tuning, incorporating weak learners such as Naive Bayes, SVM, k-NN, and Multi-Layer Perceptron (MLP). Based on results, the model is possible to predict the presence of glaucoma and non-glaucoma conditions.

6. Results and Discussion

This section implements the suggested approach to identifying critical test and training data results using database assessment metrics. We compute the accuracy and confusion matrix to assess the proposed model's correctness. Fundus images from the diabetic retinal disease and glaucoma dataset are determined using test results, F-measure, precision, accuracy, recall, F1 score, and error rate. Additionally, we perform a comparative analysis using other methods. Each system optimally estimates the confusion matrix to analyze whether an image is classified as valid (true negatives and true positives) or invalid (false negatives and false positives). Consequently, compared to other techniques such as CNN, RSOAE, DNN, and FRCNN-AAASVM, EAIHSEC method for estimating data from the confusion matrix achieved the highest accuracy in predicting diabetic retinal disease and glaucoma. For, each iteration it takes different diabetic retinal data from 1000 to 2500 and increments by 500.

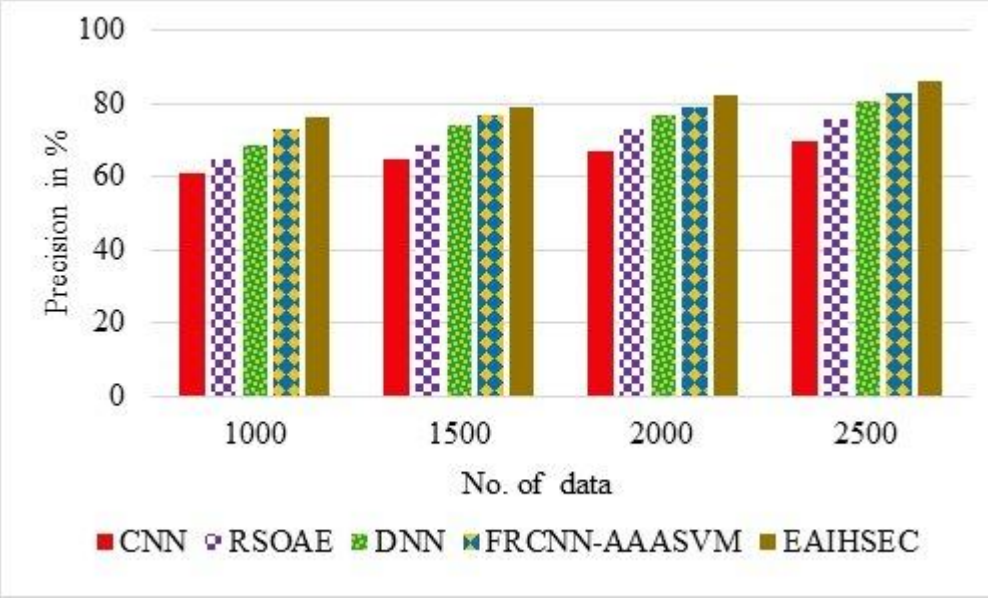

Figure 3. Analysis of the precision performance

In this section, the performance of diabetic retinal disease fundas images can be evaluated using precision analysis to determine their accuracy, as portrayed in Figure 3. The CNN, RSOAE, DNN, and FRCNN-AAASVM methods mentioned earlier have accuracies of 70%, 76%, 81%, and 83% respectively. A detailed analysis of the proposed EAIHSEC method's performance in predicting diabetic retinal disease and glaucoma disease compared to previous techniques achieves a high accuracy of 86%.

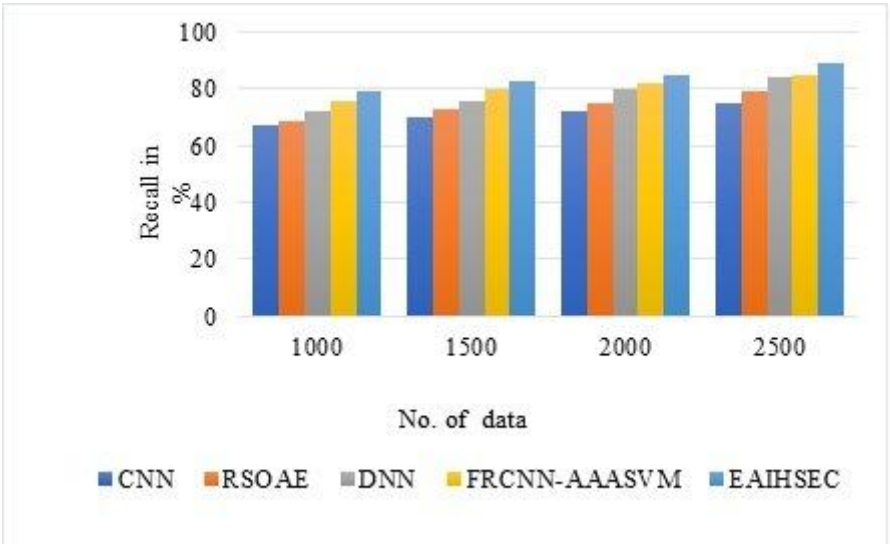

Figure 4. Analysis of the recall performance

As shown in Figure 4, recall analysis can be used to evaluate the performance of diabetic retinal disease fundas images to determine their accuracy. The CNN, RSOAE, DNN, and FRCNN-AAASVM methods mentioned earlier have ranges of 75%, 79%, 84%, and 85% respectively. A detailed analysis of the proposed EAIHSEC method's performance in predicting diabetic retinal disease and glaucoma compared to previous techniques achieves a high ratio of 89%.

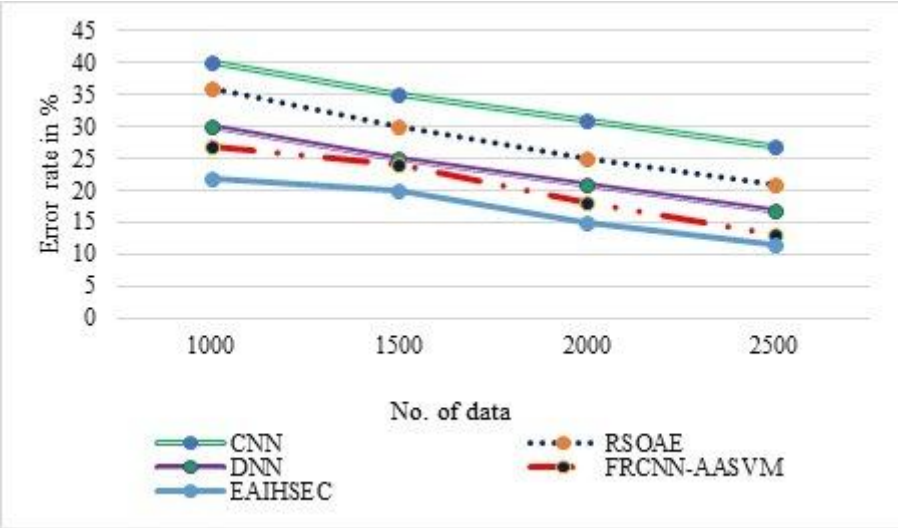

Figure 5. Performance of the error rate

As demonstrated in Figure 5, the performance ratio of the proposed algorithms in predicting the error rate of diabetic retinal fundus images can be assessed using the previous methods. The proposed EAIHSEC method yields an error rate of 11.6% when analysing these images. Compared to earlier techniques, the performance ratios are 27% for CNN, 21% for RSOAE, 17% for DNN, and 14% for FRCNN-AAASVM in predicting diabetic retinal disease and glaucoma.

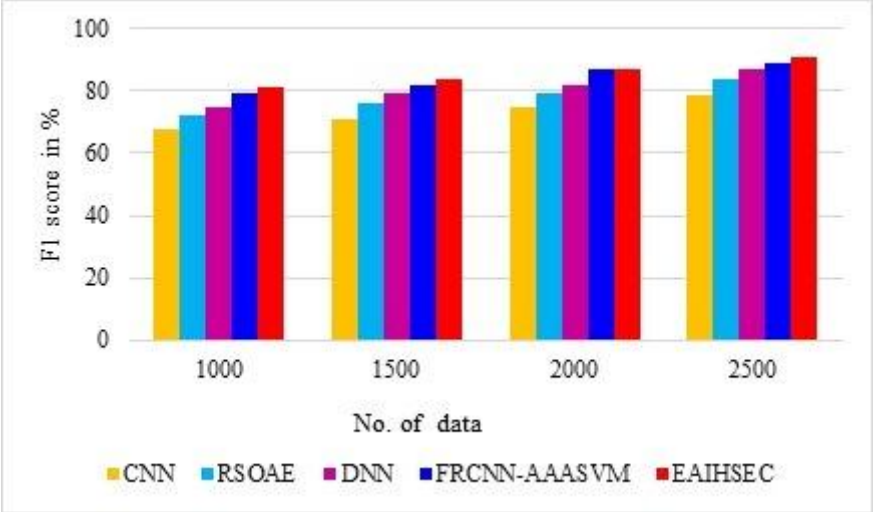

Figure 6. Analysis of the F1 score

As illustrated in Figure 6, the proposed algorithm's performance ratio in predicting the F1 score of diabetic retinal images can be evaluated using previous methods. When analyzing these images, the proposed EAIHSEC method generates an F1 score of 90.6%. Compared with the earlier techniques, the performance rate in predicting diabetic retinal disease and glaucoma was 78.9% for CNN, 83.7% for RSOAE, 86.8% for DNN, and 89% for FRCNN-AAASVM.

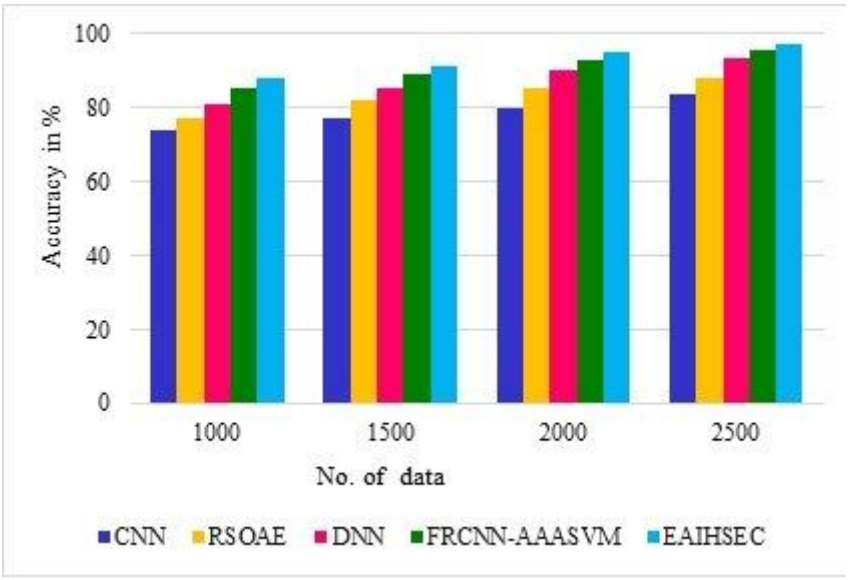

Figure 7. Performance of the accuracy

7. CONCLUSIONS

This research proposed EAIHSEC technology improved the accuracy for diabetic retinal disease and glaucoma prediction. The experimental method shows that the proposed EAIHSEC method for evaluating confusion matrix data achieves the highest accuracy of 98.3% in predicting diabetic retinal disease and glaucoma compared to other techniques such as CNN, RSOAE, BOSVM, DNN, and FRCNN-AAASVM. Correspondingly, the performance evaluation using F-measure, precision, accuracy, recall, F1 score, and error rate is determined to improve the accuracy of the proposed method using the fundus image test results. This method can be used as a decision support system for early diagnosis of glaucoma to avoid irreversible vision loss. It will be quick decision making model for clinicians.

8. ORGANIZATION OF THE THESIS

The thesis will consist of 8 chapters as described below,

Chapter 1: This chapter describes the introduction and organization of research in the prognosis of diabetic retinal disease and glaucoma. It summarizes the research problem, solving techniques, importance and impact to society.

Chapter 2: This chapter reviews a literature of various existing method and highlights different techniques, research gap identification and how to address the gaps..

Chapter 3: This chapter explains implementation of a problem through RSOAE, BOSVM, deep neural network intelligent support system for glaucoma among diabetic mellitus community.

Chapter 4: This elucidates the prediction of diabetic retinal diseases through trilayer neural network and aiming to find best activation.

Chapter 5: This chapter illustrate the designing of framework through hybrid convolutional neural network optimization with an artificial algae algorithm for glaucoma screening using fundus images and target to improve an accuracy by reducing error.

Chapter 6: This section discusses to predict diabetic retinal glaucoma based on data and image driven sustainable two-stage interpretable hybrid stacking explainable ensembles.

Chapter 7: This chapter comparing the proposed results and evaluations to assess parameters values to demonstrate performance accuracy.

Chapter 8: This final chapter summarizes the research findings, implications, and open the path for future research.

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